Journal of Economic Interaction and Coordination (2025) 20:817–841
https://doi.org/10.1007/s11403-024-00431-1

REGULAR ARTICLE

Sentiment-driven deep learning framework for insider trading detection in Indian stock market

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Received: 19 February 2024 / Accepted: 11 October 2024 / Published online: 31 October 2024

Abstract
This study presents a novel approach for identifying insider trading in the Indian stock market by integrating sentiment analysis of financial news into deep learning models, specifically single-channel convolutional neural network (1CH-CNN) and multichannel convolutional neural network (MTC-CNN). Utilizing samples of insider trading and non-insider spanning from 2001 to 2020, along with corresponding financial news from the same period, we assess the effectiveness of the proposed approach across various time windows (30, 60, and 90 days) and its capability in predicting market manipulation. Our experimental results demonstrate that models incorporating sentiment metrics outperform those without, particularly in longer time windows, exhibiting enhancements in accuracy, precision, recall, F1-score, and ROC AUC. Notably, the integration of sentiment metrics results in a 20% reduction in the false positive rate across all time windows. These findings underscore the potential of sentiment analysis in augmenting insider trading detection mechanisms, emphasizing its importance for market surveillance and investor protection within the Indian stock market.

Keywords Indian stock market · Insider trading identification · Multichannel CNN · Financial news · Sentiment analysis

1 Introduction

Detecting and preventing stock market manipulation are essential to maintain the integrity and fairness of financial markets worldwide. Maintaining a fair and transparent financial market fosters investor confidence, promotes capital formation, and

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supports economic stability (Alexander and Cumming 2022; Fletcher 2020). Among several types of manipulation, one form is insider trading, which occurs when individuals or entities trade securities based on material and non-public information about the company issuing the securities (Allen and Gale 1992; Meulbroek 1992). This practice is illegal because it gives those with insider knowledge an unfair advantage over other investors in the market (Securities and Exchange Board of India 2023; John and Narayanan 1997). Insider information can include details about earnings reports, mergers and acquisitions, regulatory decisions, or other significant events that could affect the price of a security. When insiders, such as corporate officers, directors, employees, or other individuals with access to confidential information, trade based on this privileged knowledge, they may profit at the expense of other investors who are unaware of the information. Insider trading undermines market fairness, erodes investor confidence, and violates securities laws designed to ensure transparency and integrity in financial markets (John and Narayanan 1997). Regulatory efforts globally aim to curb these issues, implementing stringent measures to enforce transparency and prevent market abuse, thus fostering a more equitable and trustworthy financial landscape. However, today's markets and trading practices are so complex and large that it is difficult to detect such events in a large population of lawful trades.

Research has been conducted extensively to study the correlation (Cohen et al. 2012), transmission mechanism of insider information (Ahern 2017), and insider trading patterns and behaviours (Tamersoy et al. 2014) using various statistical and financial models. Modern computational techniques like machine learning and deep learning have significantly contributed to this field. Early detection in option markets (Donoho 2004) using decision tree, logistic regression, and neural net models has shown promise in uncovering insider trading before public news release. Theoretical models linking insider transactions to stock return time series (Park and Lee 2010) and deep learning approaches (Islam 2018) have demonstrated improved detection rates, with minute-by-minute stock price data validating their efficacy. Techniques like XGBoost and NSGA-II (Deng et al. 2019a), GBDT and DE (Deng et al. 2019b), and outlier detection methods (Esen 2020) have also proved effective in identifying illicit trading activities. Explainable classifiers (Hsieh et al. 2010), text analytics frameworks (Liu et al. 2020), and multistage methodologies Seth and Chaudhary (2020) further enhance detection capabilities. Integration of PCA and random forest (Deng et al. 2021), multitask deep neural networks (Li et al. 2022), and machine learning on account-level transaction data (Lundblad et al. 2022) have provided valuable insights into insider trading behaviours, such as the use of multiple linked accounts during major information events. It has been observed that all these techniques employ market indicators only to identify or detect insiders, despite the fact that the sentiment from various sources such as reviews, tweets, news article or other media significantly influences the stock market movement.

Various social media platforms show a significant relation with the stock market. Duz Tan and Tas (2021) predicted relation between trading volume and returns with twitter sentiment, particularly in smaller and emerging market firms, while (Teti et al. 2019) demonstrated social media's effectiveness in predicting stock prices, especially with high coverage, and Liang et al. (2020) confirmed the significant forecasting power of social media and Internet news sentiment indices for market volatility, surpassing traditional newspapers. Conversely, sentiment analysis of textual news articles enhances the prediction of stock price forecasting models. Burggraf et al. (2020) reveal a unidirectional relationship between political news tweets from US President Donald Trump's on stock returns and the Volatility Index. In the Hong Kong Stock Exchange, models integrating both prices and news sentiments outperform those relying solely on technical indicators (Li et al. 2020). Furthermore, Li et al. (2021) illustrate how news articles influence related stocks and trigger stock co-movements through a tensor-based event-driven LSTM model in the China securities market. Sentiments derived by users from news headlines have a tremendous effect on the buying and selling patterns of the traders (Gite et al. 2021; Eck et al. 2021) and together with historical prices can be used to anticipate and prevent financial losses (Duarte et al. 2021). These collective findings underscore the potential of sentiment analysis of financial news and social media platforms to inform investment strategies and forecast market dynamics across diverse sectors and market conditions. The issue lies in sentiment metrics being exclusively utilized for forecasting rather than for the specific tasks of identification and detection, particularly in the context of insider trading detection. Analysing sentiment in financial news can enhance manipulation detection models by providing additional context on market dynamics, investor sentiment, and potential manipulative behaviour. Incorporating sentiment analysis can provide more comprehensive understanding of market movements, enabling the model to discern abnormal patterns or suspicious activities that may indicate manipulation with greater accuracy.

Leveraging the established effectiveness of sentiment analysis in various domains, including market prediction, we have devised a novel framework. This framework harnesses financial news sentiment to detect insider trading within the Indian stock market, employing a multichannel deep CNN approach. A multichannel CNN is more successful at handling multivariate time series data and has been applied in various fields ranging from health care to stock forecasting (Zhang et al. 2022; Chung and Shin 2020). Besides, multichannel convolutional neural networks (CNNs) have proved to be very effective in working with small datasets in different fields. For example, MTC-CNN has been useful in learning with small samples for recognizing facial expressions (Hamester et al. 2015), classifying disaster-related tweets (Kumar et al. 2023), and identifying lung sounds even with fewer samples (Messner et al. 2020). It has also shown success in industrial applications, like detecting faults in civil infrastructure (Shajihan et al. 2022), predicting the remaining useful life of bearings (Jiang et al. 2020), and identifying defects on solar cells with limited data (Zhang et al. 2020). These studies highlight that multichannel CNNs are reliable and valuable for various tasks where data are scarce (Liu et al.

2015). It helps to leverage the power of deep learning and convolutional operations to effectively analyse and interpret large amounts of trading data. The multichannel concept treats the variables, indicators, and sentiments as a separate channel, allowing the network to learn unique patterns and relationships among them.

As part of this study, samples from the Indian securities market are employed and a database of information is collected from a number of listed companies that have been convicted of insider trading by the SEBI (Security and Exchange Board of India) from 2001 to 2020 (Securities and Exchange Board of India 2023). For the same timeframe, news headlines and descriptions sourced from reputable news outlets like Business Standard (Standard 2024) and Times of India News (2024) are being utilized. The paper is further structured as follows: Sect. 2 details data collection methods, including news and stock information sources. Methodology is presented in Sect. 3, followed by system architecture in Sect. 4 and experimental results in Sect. 5. Finally, Sect. 6 concludes the paper. The key contributions and highlights of this research are as follows:

- A novel expert system is introduced, integrating financial news sentiment with an optimized multichannel convolutional neural network, to effectively identify insider trading in the Indian stock market.
- Among a vast array of relevant variables and indicators, 86 have been carefully selected and evaluated for their significance in identifying insider trading.
- Twenty-nine domain-specific sentiment metrics has been identified and have been employed to enhance the performance of the expert system.
- The experiments were conducted using three different time window lengths (30, 60, and 90 days) to evaluate the significance of duration in impacting the model's performance.

2 Data collection

Effective research in financial markets necessitates a careful approach to data collection, ensuring the reliability and comprehensiveness of the information under scrutiny. This section details the sources used to gather news and stock-related data, emphasizing the significance of each dataset in providing a holistic understanding of market dynamics.

2.1 News data source

The study utilized news articles sourced from Business Standard (Standard 2024) and Times of India News (2024) in coordination with existing dataset from Kaggle (India News Headlines Dataset 2024; Indian financial news articles 2024). Kaggle, a widely recognized platform, holds reputation for diverse datasets, and has been

Table 1 Sentiment metrics

Category	Sentiment metrics	Description
Financial sentiments	Financial up (finup)/bullish, financial hype (finhype), financial down (findown)/bearish	Reflect investor perceptions of market trends and asset values, influencing buying and selling decisions
Modal sentiments	Modal weak, modal strong	Capture public opinions and attitudes, often shaping cultural and social narratives
Market and economic sentiments	Inflationary sentiments, earnings optimism, earnings concerns, market volatility, mergers and acquisitions enthusiasm, regulatory and policy optimism, regulatory and policy concerns, economic outlook optimism, economic concerns	Gauge collective views on economic conditions, impacting consumer behaviour and investment activities
Geopolitical and news catalyst sentiments	Geopolitical tensions, market optimism due to news catalyst, market concerns due to news catalyst	Measure reactions to global events and news, influencing market volatility and geopolitical risk assessments
Corporate and trade sentiments	Sentiment on corporate governance, sentiment on trade agreements, sentiment on currency markets, sentiment on financial health	Assess sentiments surrounding specific companies and trade relations, affecting stock prices and market dynamics
General sentiments	Positive, negative, litigious	Encompass a broad spectrum of public emotions and attitudes, providing insight into overall societal mood
Aggregated and miscellaneous sentiments	Aggregated sentiment, interrogative sentiment, relative volume of talk (RVT), fear, related market measures	Include diverse sentiments not covered in specific categories, contributing to a comprehensive understanding of public sentiment trends

widely utilized in the field of academia and research (Muhammad et al. 2020; Sujatha and Reddy 2023; Manikandan et al. 2024). The compiled dataset spans news headlines and descriptions from 2001 to 2020, offering ample data for analysis. These sources are acknowledged for insightful coverage of market events related to the Indian economy, highlighting the significance of selecting reputable data for a reliable understanding of contextual factors influencing financial markets in the analysis.

Sentiment analysis is a vital part of comprehending market dynamics, involving the evaluation of emotional tones in textual data. In our study, we use sentiment metrics associated with specific lexicons or dictionaries. Table 1 outlines these metrics, covering various financial sentiments such as bullish and bearish outlooks, considerations of volatility, geopolitical tensions, corporate governance, and more. Each sentiment metric corresponds to a lexicon or dictionary that defines indicative words. For example, the "Financial Up" sentiment includes positive terms like rise, gain, and uptrend. The lexicons for these metrics are provided in Appendix 1. This structured approach facilitates a nuanced analysis, allowing the model to effectively incorporate diverse emotional responses from financial news articles. The use of these metrics is crucial for assessing contextual nuances, contributing to a more comprehensive understanding of market sentiment.

2.2 Stock information source

The foundation of stock market research relies on obtaining accurate and reliable data from reputable sources. In this study, the insider trading samples for experiments are obtained from SEBI (Securities and Exchange Board of India), BSE (Bombay Stock Exchange), and NSE (National Stock Exchange of India Ltd), and the related indicators of insider trading samples are obtained from the CMIE (Centre for Monitoring Indian Economy) (Securities and Exchange Board of India 2023; NSE 2023; BSE (formerly Bombay Stock Exchange) 2023; CMIE 2023). These platforms are recognized for providing comprehensive and up-to-date information related to securities, market trends, and financial indicators.

The analysis encompassed various features, such as variables and indicators, derived from the aforementioned stock information sources. These features were thoughtfully selected to encompass diverse aspects of market dynamics, offering a holistic view of insider trading patterns in the Indian stock market. Specifically, Table 2 provides a detailed list of features relevant to insider trading, including price-related, volume-related, trend and direction, volatility and bands, oscillators, risk-related, and miscellaneous categories. These features were chosen to capture a comprehensive understanding of market behaviour and contribute to a nuanced analysis of insider trading patterns in the Indian stock market.

Table 2 A list of features (variables and indicators)

Category	Features	Description
Price-related	Prev Close; Open Price; High Price; Low Price; Last Traded Price; Close Price	Reflects the historical and current pricing of securities, essential for understanding market movements and trends
Volume-related	Total Traded Quantity; No. of Orders; Deliverable Quantity; On-Balance Volume (OBV)	Provides insights into the trading activity, indicating the level of interest and participation in the market
Trend and direction	Close Location Value (CLV); Accumulation/Distribution (AD); Difference Moving Up (DM +); Difference Moving Down (DM-); True range (TR); Directional Trend (DM14 +); Directional Trend (DM14-); Directional Indicator (DI14 +); Directional Indicator (DI14-); Directional Index (DX); Average Directional Movement Index (ADX); Exponential Moving Average (EMA)	Helps identify trends, trading volumes, and potential reversal points in the market
Volatility and bands	Sigma Coefficient; Standard deviation(σ30); Bollinger Upper Band; Bollinger Lower Band; Chaikin Money Flow (CHMF); Chaikin Volatility (CHV)	Measures the strength of a trend and its potential continuation or reversal
Oscillators	Commodity Channel Index (CCI); Full Stochastic %K (Fast FS); Full Stochastic %D (Full FS); Price Oscillator (POS); Relative Strength Index (RSI); Relative Strength (RS)	Quantifies the trend's strength and assists in understanding market direction
Risk-related	Security VaR; Nifty 50 Close price; Index Value at Risk (IVaR); Floating Stock Turnover Rate (FSTR); Total Share Turnover Rate (TSTR); Excess Return Compared with Same Market (ERCSM)	Indicates market volatility and potential trading opportunities, offering insights into price movements
Miscellaneous	Typical Price (TP); Detrended Price Oscillator (DPO); Ease of Movement (EMV); Fibonacci Retracement (FR); Fibonacci Extension (FE); Money Flow Index (MFI); Moving Average Convergence Divergence (MACD); Pivot Point (PP); First Support (S1); Second Support (S2); Third Support (S3); First Resistance (R1); Second Resistance (R2); Third Resistance (R3); Rate of Change (ROC); Williams %R (%R)	Measures momentum, overbought or oversold conditions, aiding in identifying potential market turning points

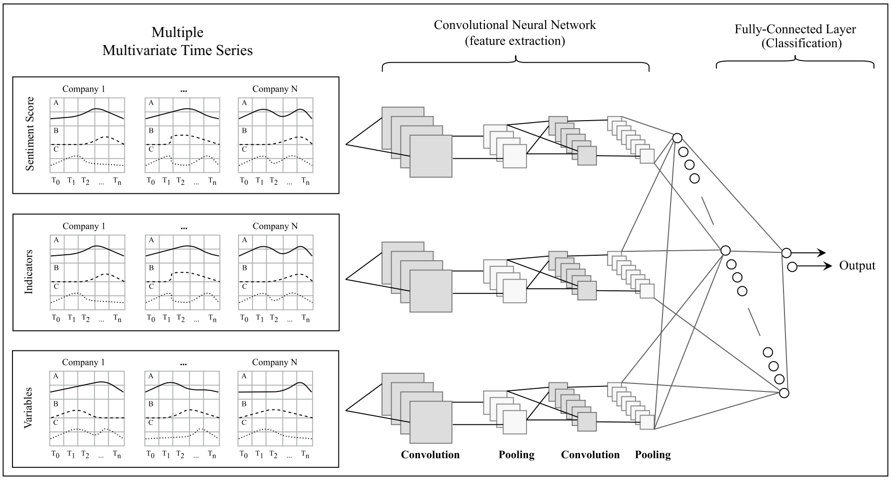

Fig. 1 Multichannel CNN structure with sentiment score as independent channel

3 Methodology

3.1 Multichannel CNN

Multichannel CNN (MTC-CNN) is essentially a CNN with multiple input channels, where each input channel corresponds to a different type of feature or data as shown in Fig. 1. For example, in an image classification task, an RGB image with three colour channels can be processed by a multichannel CNN, where each channel is treated as a separate input channel. The CNN can learn to extract different features from each colour channel, which can help to improve the overall accuracy of the classification. Similarly, in a speech recognition task, a multichannel CNN can be used to process multiple acoustic features such as spectrograms, Mel-frequency cepstral coefficients (MFCCs), and pitch contours as separate input channels. The use of multiple input channels can provide richer information to the network, allowing it to learn more complex features and patterns in the data. This makes multichannel CNNs a powerful tool for a wide range of applications in deep learning, including image processing, speech recognition, and natural language processing.

In the detection of insider trading, a multichannel CNN is used to process multiple indicators and variables associated with trading data in addition to the sentiment score generated from the financial news. Each indicator, variable, and sentiment is treated as a separate channel, allowing the network to learn unique patterns and relationships among them. This approach helps the multichannel CNN to capture complex interactions and dependencies among different channels, potentially enhancing the accuracy of identifying insider trading activities. The network learns to extract important features from each channel and combines them to make predictions, enabling it to detect subtle patterns and anomalies that might indicate instances of insider trading. As illustrated in Fig. 1, the model utilizes a three-channel structure to capture variable, indicator, and sentiments, offering a comprehensive perspective for enhanced financial data classification.

In the methodology, a comparative analysis is conducted between single- and multichannel configurations. For single-channel CNNs, models based on variables and indicators (1CH-CNN: Variable + Indicator) are compared with the extended model incorporating sentiment analysis (1CH-CNN: Variable + Indicator + Sentiment). In the multichannel paradigm, configurations such as MTC-CNN (Variable + Indicator) and MTC-CNN (Variable + Indicator + Sentiment) are investigated. This comparative exploration aims to elucidate the impact of incorporating sentiment analysis through multiple channels, providing insights into the efficacy of multichannel convolutional neural network in the context of stock market manipulation detection.

3.2 Sentiment score alignment: a padding approach

Sentiment analysis, a pivotal task in natural language processing, aims to discern the underlying sentiment or emotional tone conveyed in text data. Among the plethora of approaches, lexicon-based methods stand out for their simplicity, transparency, and efficiency (Jurek et al. 2015; Asghar et al. 2019; Turney and Littman 2003). By leveraging pre-defined dictionaries of words and their associated sentiment scores, these methods offer a pragmatic solution for sentiment classification. Through this approach, words are assigned sentiment polarities, enabling the analysis of text sentiments based on the aggregation of these scores.

$$\text{Sentiment Score(SC)} = \frac{\sum_{i=1}^{n} \text{score}(w_i)}{n}; \quad \text{for } i \leq n$$

where n is the total number of words in the news description, including the headlines, for a single day; and w_i is the total number of lexicons present in the text.

We employed a lexicon-based method to calculate sentiment scores from daily financial news articles. This involved utilizing a curated lexicon of finance-related words and their associated sentiment polarities. In our case, we assigned an equal polarity to each lexicon. Each word in the news articles was matched with entries in the lexicon, and sentiment scores were assigned accordingly. The sentiment scores for individual words were then aggregated to derive an overall sentiment score for each news article.

After computing the sentiment scores (denoted as SS) for each sentiment metric (SM), as illustrated in Fig. 2, we left with a sentiment channel of dimension 29*N, where N represents the window length. Following the generation of the sentiment

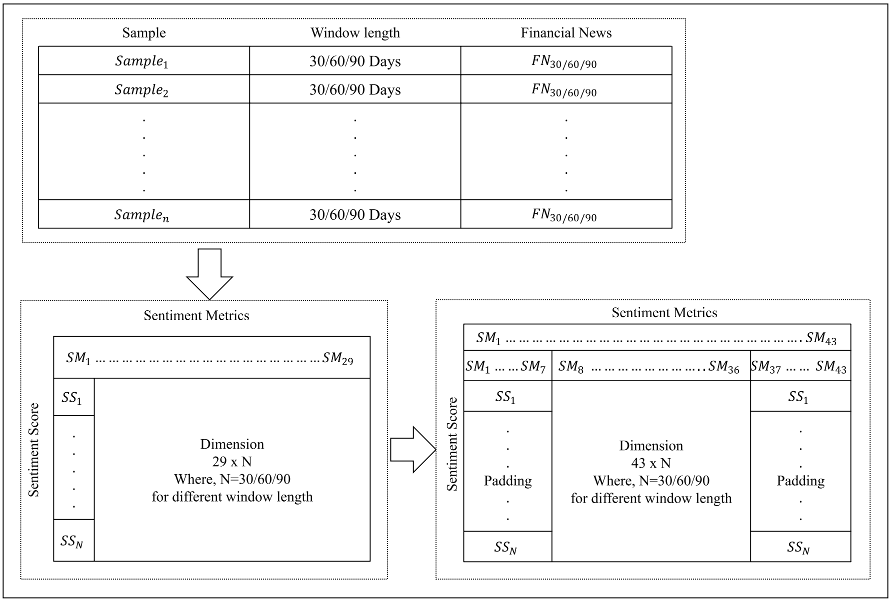

Fig. 2 Sentiment channel derived from the financial news incorporating padding approach

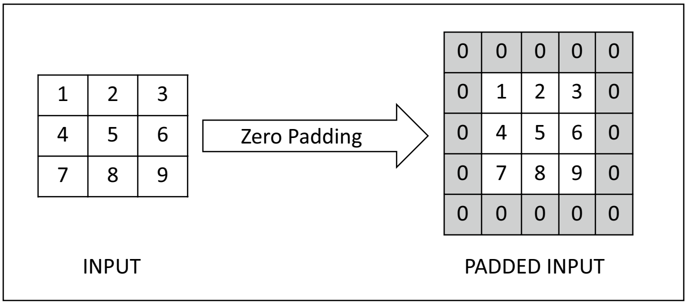

Fig. 3 Padding approach

channel, it was augmented through padding to ensure alignment with the dimensions of the variable and indicator channels, resulting in a uniform structure of 43*N, as depicted in Fig. 2. This alignment is crucial for maintaining consistency and compatibility across all channels, facilitating seamless integration and subsequent analysis of the combined dataset. By harmonizing the dimensions of the sentiment channel with those of the variable and indicator channels, we enable comprehensive and cohesive exploration of the entire dataset, fostering a holistic understanding of the interrelationships between sentiment dynamics, financial variables, and indicators within the analysed context.

A padding approach is a common modification in CNN design, involving symmetrically adding zeros to the input matrix as shown in Fig. 3. This adjustment allows the size of the input to meet specific requirements, particularly when the dimensions of the input volume need to be preserved in the output volume. Padding improves the model performance compared to the original configuration (Wiranata et al. 2018), especially padding with estimated background while maintaining aspect ratio, and leads to higher classification accuracy compared to direct resizing (Shahnaz and Mollah 2023). The technique has shown positive impact on the performance and accuracy of long short-term memory (LSTM) networks and convolutional neural networks (CNN) in sentiment analysis tasks (Dwarampudi and Reddy 2019), emphasizing the importance of proper padding for input sequences. Padding in convolutional neural networks for natural language processing tasks significantly improves sentiment analysis results over no padding strategy, even surpassing state-of-the-art performance (Giménez et al. 2020).

The incorporation of sentiment scores into the model requires a mechanism to align the sentiment data with variable and indicator metrics. To maintain a consistent format, the sentiment score matrix undergoes adjustment using a padding method shown in Fig. 2. This method involves adding elements, typically represented as zeros or another specified value, at both the beginning and end of the sentiment matrix. The objective is to create a sentiment score matrix with dimensions of 43*N, where N represents the window length. Figure 2 clearly shows that SM1-to-SM7 and SM37-to-SM49 are padded element with the sentiment score ranging from SM8-to-SM36. Hence, the technique transforms the dimension of sentiment channel of 29*N to 43*N ensuring the alignment of sentiment data with the structure of variable and indicator metrics, facilitating a uniform and compatible integration within the model.

3.3 Performance metrics for the proposed study

In this section, we discuss the metrics employed to assess the model's performance and its capability to identify insider trading in the Indian stock market.

Accuracy is a popular metric used in classification problems. It provided us the ratio of correctly predicted instances to the total instances.

$$\text{Accuracy} = (\text{TP} + \text{TN} + \text{FP} + \text{FN})/(\text{TP} + \text{TN})$$

where TP (true positive) is the correctly identified instances of insider trading; TN (true negative) is the correctly identified instances of non-insider trading; FP (false positive) is the incorrectly identified instances of insider trading; and FN (false negative) is the incorrectly identified instances of non-insider trading.

Precision is the ratio of correctly predicted positive observations to the total predicted positive observations.

$$\text{Precision} = \text{TP}/(\text{TP} + \text{FP})$$

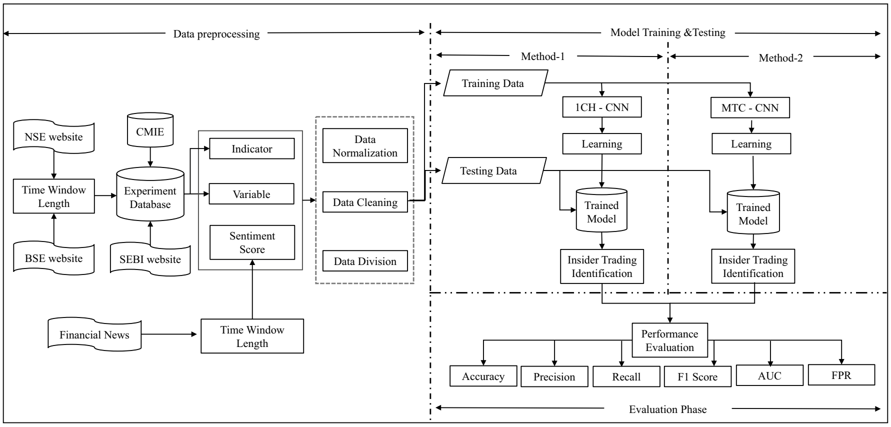

Fig. 4 Illustration of the proposed approach for identifying insider trading in the Indian stock market

Recall (sensitivity or true positive rate) is the ratio of correctly predicted positive observations to the all observations in actual class.

$$\text{Recall} = \text{TP}/(\text{TP} + \text{FN})$$

F1-score is the harmonic mean of precision and recall.

$$\text{F1 Score} = 2 \times (\text{Precision} \times \text{Recall})/(\text{Precision} + \text{Recall})$$

ROC AUC (receiver operating characteristic area under curve) is a probability curve, and AUC represents the degree or measure of separability. It indicates how well the model distinguishes between classes. A higher AUC value indicates better model performance.

4 System architecture

The system architecture, as illustrated in Fig. 4, initiates with a critical phase of data pre-processing. The initial stage of data pre-processing involves constructing the experimental dataset used for training, testing, and validating the proposed intelligent system. The study employed a dataset encompassing insider trading cases spanning from 2001 to 2020, sourced from the SEBI website (Securities and Exchange Board of India 2023). To ensure balance, an equivalent number of non-insider samples were also incorporated, creating a 1:1 ratio of illegal insider trading to non-insider trading instances. In total, there were 30 samples, with 15 instances of insider trading and 15 instances of non-insider trading. The selection criteria for these samples were as follows: (1) the listed companies belonged to the same industry as the insider trading cases, and (2) the non-insider trading cases had no history of insider trading activity. This selection process ensures that the samples accurately represent the two categories. Stock exchange websites BSE, NSE, and CMIE's Prowess

IQ database were used to collect equity data for all samples (NSE 2023; BSE (formerly Bombay Stock Exchange) 2023; CMIE 2023). Variables represent measurable quantities or characteristics, while indicators are derived metrics or signals that provide insights into specific aspects of insider trading. On the contrary, financial news data were obtained from Business Standard (Standard 2024), Times of India (News 2024) and Kaggle (India News Headlines Dataset 2024; Indian financial news articles (2003–2020) 2024), covering the period from 2000 to 2020. Sentiment analysis was performed using a padding technique to align the datasets as shown in Figs. 2 and 3.

To make sure the data are reliable and suitable for analysis, it goes through a next stage of pre-processing process that involves organizing and checking the data to ensure its quality. To test the multicollinearity between the variables, a Pearson's correlation coefficient (PCC) statistical test is carried out with a cut-off of 0.70 for identifying and discarding irrelevant features. To boost our model's efficiency and reliability, we applied the min–max normalization method for scaling features to account for a significant number of market fluctuations and trade noises. A total of 96 features (variables and indicators) were collected out of which 10 features were excluded from the analysis due to insufficient observations, multicollinearity, and the requirement to split these variables and indicators equally making it a total of 86 features. Conversely, we identified 29 sentiment metrics and augmented them with a padding technique, resulting in a final count of 43 metrics.

After the pre-processing stage, usually the dataset is portioned into training and testing sets, a pivotal step in model evaluation. However, while working with a small dataset, it becomes challenging to split the data into traditional training, testing, and validation sets while ensuring reliable model evaluation. K-fold cross-validation is known for maximizing data utilization, balance bias, and variance in performance evaluation, and detecting overfitting or underfitting. This technique enables a thorough evaluation of our method's performance and generalizability, showcasing our commitment to extracting the most from our limited samples. Hence, K-fold cross-validation technique has been used that repeatedly split the data into training and testing allowing a more comprehensive evaluation by leveraging all available data.

Two distinct methods, namely the single-channel convolutional neural network (1CH-CNN), i.e. Method-1, and multichannel convolutional neural network (MTC-CNN), i.e. Method-2, are employed. The 1CH-CNN model integrates stock variables, indicators, and sentiment scores within a single channel. In contrast, the MTC-CNN model utilizes separate channels for each of these components, as illustrated in Fig. 4. After performing dataset pre-processing, the hyperparameters of the CNN model were fine-tuned. The model was trained using optimized parameters. The goal of this optimization process is to find the best set of hyperparameters that yield the highest performance for our MTC-CNN model. The optimization process resulted in the selection of a convolutional layer with a (3,3) kernel size and ReLU activation function as part of the best hyperparameter set. The MTC-CNN model is designed to process time series data with different time windows, namely 30 days, 60 days, and 90 days. Each time window configuration has different hyperparameters for its layers shown in Table 3. The

Table 3 MTC-CNN optimized parameter

Time window	Convolution layer			Dropout_1	Fully connected layer		Dropout_2	Final output layer	
	Layer	Kernel size	Activation function		Dense	Activation function		Dense	Activation function
30 days	52	(3,3)	ReLU	0.5	58	ReLU	0.5	1	Sigmoid
60 days	22	(3,3)	ReLU	0.5	59	ReLU	0.5	1	Sigmoid
90 days	19	(3,3)	ReLU	0.5	25	ReLU	0.5	1	Sigmoid

pseudocode for the proposed MTC-CNN model is shown in Algorithm 1. The subsequent performance analysis involves the assessment of key metrics such as accuracy, precision, recall, F1-score, AUC, and false positive rate (FPR). These metrics collectively gauge the effectiveness of the models in capturing and predicting market trends based on the integrated sentiment scores. This systematic approach ensures a robust evaluation of the models' predictive capabilities and their potential contributions to market analysis.

Algorithm 1 Multichannel convolutional neural network (MTC-CNN)

1 : **algorithm** Multichannel-CNN
2 : **input:** input1: 3D matrix (wl, 43, 1), input2: 3D matrix (wl, 43, 1), input3: 3D matrix (wl, 43, 1)
3 : **output:** Score of Multichannel-CNN trained model on the test dataset
4 : **let** conv1 be the result of $Conv2D(32, kernel\_size = (3,3), activation =' relu')$(input1)
5 : **let** conv2 be the result of $Conv2D(32, kernel\_size = (3,3), activation =' relu')$(input2)
6 : **let** conv3 be the result of $Conv2D(32, kernel\_size = (3,3), activation =' relu')$(input3)
7 : **let** concat be the result of $Concatenate()$([conv1, conv2, conv3])
8 : **let** dropout1 be the result of $Dropout(0.5)$(concat)
9 : **let** flat be the result of $Flatten()$(dropout1)
10 : **let** fc be the result of $Dense(64, activation =' relu')$(flat)
11 : **let** dropout2 be the result of $Dropout(0.5)$(fc)
12 : **let** output be the result of $Dense(1, activation =' sigmoid')$(dropout2)
13 : **let** model be the result of Model(inputs=[input1, input2, input3], outputs=output)
14 : **Compile** model using $optimizer =' adam', loss =' binary\_cross\_entropy', metrics = ['accuracy']$
15 : **let** f be the featureset 3D matrix
16 : **for** each sample i in the dataset **do**
17 : **let** f_i be the featureset matrix of sample i
18 : **for** each channel j in i **do**
19 : **let** V_j be the result of $Conv2D(32, kernel\_size = (3,3), activation =' relu')(j)$
20 : **append** V_j *to* f_i
21 : **append** f_i *to* f
22 : $f_{train}, f_{test}, I_{train}, I_{test}$ be the result of splitting feature set and labels into train subset and test subset
23 : **let** M be the result of creating Multichannel-CNN model using (f_{train}, I_{train})
24 : **let** score be the result of evaluating the model on test data (f_{test}, I_{test})
25 : **return** score

5 Experimental results

In our study, we compared the performance of two deep learning models, CH-CNN (V+I+S) and MTC-CNN (V, I, S), to understand how different combinations of channels impact the detection of insider trading. Below, we provide a detailed explanation of the differences between these models and their implications for network architecture and performance.

CH-CNN (V+I+S) The CH-CNN (V+I+S) model integrates variables (V), indicators (I), and sentiment scores (S) into a single concatenated input. This approach involves the following steps:

Concatenation of Features: The variables, indicators, and sentiment scores are combined into a single feature vector. This concatenated input is then fed into the convolutional neural network (CNN).

Early Integration: By combining all features at the input stage, the network learns the interactions between variables, indicators, and sentiment scores from the beginning. This early integration allows the network to potentially capture complex dependencies and interactions among the different types of data.

Network Architecture: The CNN processes the concatenated input through multiple convolutional and pooling layers, learning hierarchical feature representations. The integrated features are then passed through fully connected layers to make the final prediction.

MTC-CNN (V, I, S) The MTC-CNN (V, I, S) model, in contrast, treats each channel separately and employs a multitask convolutional neural network architecture. The key steps in this approach are:

Separate Processing of Channels: The variables, indicators, and sentiment scores are processed independently by separate CNNs. Each CNN is specialized in learning features from its respective channel.

Independent Feature Extraction: By using separate CNNs, the network preserves the unique characteristics of each type of data. The variables CNN focuses on extracting patterns from variables, the indicators CNN from indicators, and the sentiment CNN from sentiment scores.

Late Integration: The features extracted by the separate CNNs are integrated at a later stage in the network. This is typically done by concatenating the outputs of the individual CNNs and passing them through additional layers to make the final prediction. This approach allows the network to first learn specialized features for each channel and then combine them to form a holistic representation.

Network Architecture: The MTC-CNN architecture consists of multiple parallel CNNs, each dedicated to one of the channels (V, I, or S). The outputs of these CNNs are then merged and further processed through fully connected layers to generate the final prediction.

The primary difference between CH-CNN (V+I+S) and MTC-CNN (V, I, S) lies in the stage at which feature integration occurs. CH-CNN (V+I+S) integrates features early, allowing the network to learn complex interactions from the start. This can be beneficial when the interactions between different types of data are crucial for the task. On the other hand, MTC-CNN (V, I, S) integrates features later, preserving the unique characteristics of each type of data during the initial stages of processing. This can lead to better performance when the distinct features of each channel are important and need to be learned independently before combining. In our experiments, we found that the choice of model architecture significantly

Table 4 Accuracy results

Time window	1CH-CNN (V+I) (%)	1CH-CNN (V+I+S) (%)	MTC-CNN (V, I) (%)	MTC-CNN (V, I, S) (%)
30 days	75.00	75.00	87.50	75.00
60 days	62.50	87.50	75.00	75.00
90 days	50.00	87.50	62.50	75.00

impacts the performance of insider trading detection. The detailed accuracy results are provided in Table 4, providing insights into the advantages and limitations of each approach. We aim to provide a deeper understanding of how the combination and integration of channels influence the architecture and performance of deep learning models for financial applications.

From the provided accuracy results in Table 4, we can observe that for the 30-day window length, both concatenating sentiment scores with financial variables and indicators, i.e. 1CH-CNN, and incorporating them as separate input channels, i.e. MTC-CNN, resulted in no improvement or even degradation in model performance, maintaining an accuracy of 75.00%. This is likely due to the high noise and variability inherent in short-term sentiment data, which fails to provide additional predictive power and may introduce confusion. In contrast, in a 60-day window length we can observe a remarkable increase in accuracy to 87.50% for 1CH-CNN, highlighting the added value of more stable and meaningful sentiment trends over this period. However, when processed as MTC-CNN, the performance remained at 75.00%, indicating that the model architecture might not fully exploit the sentiment data in this configuration. For the 90-day window length, the accuracy similarly improved to 87.50% with concatenated inputs, demonstrating the robustness and relevance of long-term sentiment trends. Separate input channels in this case achieved an accuracy of 75.00%, again suggesting that while longer-term sentiment scores are beneficial, the model's ability to integrate them effectively depends on how the data are presented. These findings underscore the importance of selecting appropriate time windows for sentiment data and the method of integration to enhance the predictive capabilities of CNN models in financial forecasting or in a case of identifying insider trading in the Indian stock market.

Overall, the model 1CH-CNN with sentiment channel outperforms the one without it, achieving an accuracy of 87.50% compared to 62.50% and 50.00% in both the windows except 30 days. This suggests that incorporating sentiment analysis improves the accuracy of the model, particularly for longer time windows. In the case of MTC-CNN with sentiment channel outperforms the one without it only in the 90-day window, suggesting that sentiment analysis of financial news has a substantial positive impact on the accuracy of insider trading detection, particularly for longer time windows like 60 or 90 days. Comparing the accuracy of models with and without sentiment analysis for the 90-day time window, we can see a significant improvement when sentiment analysis is included. It implies that longer-term trends and sentiments expressed in financial news articles provide valuable information for detecting insider trading activities. On the other hand, the proposed MTC-CNN

Table 5 Precision results

Time window	1CH-CNN (V+I) (%)	1CH-CNN (V+I+S) (%)	MTC-CNN (V, I) (%)	MTC-CNN (V, I, S) (%)
30 days	66.66	66.66	75.00	60.00
60 days	50.00	75.00	100.00	100.00
90 days	42.85	66.66	50.00	66.67

outperforms the 1CH-CNN, achieving an accuracy of 87.50% compared to 75.00% in 30-day, 75.00% compared to 62.50% in 60-day, and 62.50% compared to 50.00% in 90-day window length advocating the success of multichannel over single-channel CNN.

Table 5 presents precision results for the compared models, highlighting their performance in identifying true positive cases of insider trading while minimizing false positives. The precision metric is crucial for assessing the reliability of a model in correctly classifying instances of insider trading. A significant improvement in precision can be seen for the 60-day and 90-day window, indicating that sentiment analysis might provide more context or information for longer-term trading patterns. This suggests that incorporating sentiment analysis of financial news has a particularly positive impact on identifying insider trading when looking at longer time windows such as 90 days. This could be due to the fact that longer-term trends and market sentiments are better captured and analysed through sentiment analysis of financial news. On the other hand, the proposed MTC-CNN outperforms the 1CH-CNN, achieving a precision accuracy of 75.00% compared to 66.66% in 30-day, 100.00% compared to 50.00% in 60-day, and 50.00% compared to 42.85% in 90-day window length advocating the success of multichannel over single-channel CNN.

Table 6 offers a comprehensive performance comparison, evaluating key metrics including recall, F1-score, ROC AUC, and FPR for each model across different time windows. These metrics provide a nuanced understanding of the models'

Table 6 Performance comparison of models for insider trading classification

Time window	Model	Recall (%)	F1-score (%)	ROC AUC (%)	FPR (%)
30 days	1CH-CNN (V+I)	66.66	66.66	73.33	20.00
	1CH-CNN (V+I+S)	50.00	50.00	66.66	00.00
	MTC-CNN (V, I)	100.00	85.71	90.00	20.00
	MTC-CNN (V, I, S)	33.33	50.00	66.67	00.00
60 days	1CH-CNN (V+I)	100.00	66.66	70.00	60.00
	1CH-CNN (V+I+S)	66.67	80.00	83.33	00.00
	MTC-CNN (V, I)	33.33	50.00	66.66	20.00
	MTC-CNN (V, I, S)	66.67	75.00	80.00	00.00
90 days	1CH-CNN (V+I)	100.00	60.00	60.00	20.00
	1CH-CNN (V+I+S)	50.00	80.00	83.33	00.00
	MTC-CNN (V, I)	100.00	66.66	70.00	60.00
	MTC-CNN (V, I, S)	66.67	66.67	73.33	40.00

effectiveness in insider trading classification, considering both true positive rates, overall model accuracy, and the ability to minimize false positives. For 30-day time window, both 1CH-CNN(V + I) and MTC-CNN (V, I) have relatively high recall and F1-score, indicating good performance in identifying insider trading. The addition of sentiment channel to 1CH-CNN(V + I) seems to decrease the performance significantly maybe due to the smaller time window. FPR decreases by 20% for both the 1CH-CNN and MTC-CNN after incorporating the sentiment feature.

For 60-day time window, both 1CH-CNN(V + I) and 1CH-CNN(V + I + S) show improvements in recall and F1-score compared to the 30-day window. The addition of sentiment analysis seems to positively impact the performance of 1CH-CNN(V + I + S). ROC AUC scores are higher for models incorporating sentiment analysis. MTC-CNN models show mixed performance, with varying recall and F1-score. However, FPR decreases by 20% for both the 1CH-CNN and MTC-CNN after incorporating the sentiment feature.

For 90-day time window, the addition of sentiment analysis slightly improves the F1-score for 1CH-CNN(V + I + S) in the 90-day window and maintains perfect recall, indicating it always identifies all relevant instances. MTC-CNN models show consistent performance, with relatively lower recall compared to 1CH-CNN but higher F1-scores. FPR decreases by 20% for both the 1CH-CNN and MTC-CNN after incorporating the sentiment feature. Inferentially, the positive impact of financial news sentiment seems more prominent in longer time windows (90 days). This could be because sentiment analysis captures long-term trends and market sentiments better, providing more meaningful insights for insider trading detection over extended periods.

6 Discussion

The findings of this study underscore the potential of incorporating sentiment analysis of financial news into deep learning models for improving insider trading detection in financial markets. The experimental results, as demonstrated in Tables 4, 5, and 6, provide empirical evidence of the effectiveness of the proposed approach. The comparative analysis indicates superior performance in 90-day windows, showcasing the model's ability to provide more accurate and reliable predictions over extended periods. Notably, models augmented with sentiment scores exhibit superior performance compared to their counterparts, highlighting the value of leveraging sentiment analysis in enhancing predictive capabilities.

While the integration of sentiment analysis presents promising outcomes, challenges persist. One significant hurdle is the interpretability of deep learning models, particularly in complex architectures like neural networks. Overcoming this challenge is essential for enhancing transparency and trust in the models' decision-making processes.

Moving forward, future research should explore innovative solutions to address these challenges and capitalize on opportunities for further improvement. Supporting multiple languages, refining pre-trained models on financial data, and exploring alternative approaches for integrating sentiment signals are avenues worth exploring.

7 Conclusion

In conclusion, this study advances the field of insider trading detection by leveraging sentiment analysis of financial news within deep learning models. The framework proposed in this research demonstrates promising results in improving the accuracy and reliability of insider trading detection mechanisms.

While challenges remain, particularly regarding model interpretability, this research lays the foundation for future advancements in market surveillance and investor protection. By addressing these challenges and capitalizing on opportunities for refinement, the integration of sentiment analysis into deep learning models holds great potential for enhancing market integrity and fostering investor confidence in financial markets.

Appendix 1: sentiment metrics with lexicon

Sentiments metrics	Lexicon
Financial up (finup)/bullish	Rise, gain, upward, strong, uptrend, growth, boom, bullish, increase
Financial hype (finhype)	Sensationalism, overvalued, exuberance, hot stock, run-up, wild ride, market surge, buying spree, irrational exuberance, renzy, mania, hype, bubble, speculation, excitement, euphoria, craze, amazing profits, unbelievable growth, unprecedented success
Financial down (findown)/bearish	Downturn, decline, slump, bearish, weak, fall, loss, decrease
Modal weak	Fragile, feeble. Vulnerable. Fragility
Modal strong	Robust, resilient, vigorous, strength
Inflationary sentiments	Inflation, devaluation, unemployment, purchasing power, cost rise, inflation fears, hyperinflation, asset inflation, economic overheating, wage inflation
Earnings optimism	Profit outlook, income growth, bullish earnings, earnings surge
Earnings concerns	Profit warning, income drop, earnings disappointment, earnings slump
Market volatility	Price swings, volatile markets, market turbulence, market instability
Mergers and acquisitions enthusiasm	Acquisition, merger, integration, valuation, takeover, dilution, restructuring, divestiture, synergy, valuation, deal
Regulatory and policy optimism	Regulation support, policy positivity, optimistic regulations, policy benefits, compliance, reforms, supportive, favourable, investment-friendly, regulations, government support, legal framework, economic policy, regulatory environment, rule of law, pro-growth policies
Regulatory and policy concerns	Regulation hurdles, policy uncertainty, regulatory risks, policy challenges, regulatory hurdles, regulatory scrutiny, policy ambiguity, legal challenges, compliance costs, regulatory changes, policy uncertainty, compliance burden, regulatory constraints, policy instability, regulatory risk, government intervention, legal restrictions, market apprehension, policy unpredictability, regulatory compliance issues, rule changes

Sentiments metrics	Lexicon
Economic outlook optimism	Economic growth, positive outlook, prosperity, economic expansion, prosperity, confidence, recovery, expansion, upturn, upbeat, promising, optimistic forecasts, investment opportunities, market enthusiasm, fiscal stimulus, business confidence, consumer spending, asset appreciation, bright outlook
Economic concerns	Economic slowdown, economic risks, downturn fears, economic instability, recession, downturn, contraction, crisis, deflation, economic slowdown, consumer confidence, budget deficit, trade tensions
Geopolitical tensions	Global conflicts, international tensions, geopolitical uncertainty, security concerns, trade disruptions, geopolitical events, diplomatic issues, foreign policy, international relations, regional disputes, economic sanctions, geostrategic concerns, defence spending, sovereignty issues, national security
Market optimism due to news catalyst	Market boost, investor confidence, upward momentum, news-driven optimism, anticipation, speculation, positive news flow, favourable developments, investor enthusiasm, price surge, market euphoria, buying frenzy, trading excitement, performance boost
Market concerns due to news catalyst	Market downturn, selloff, repercussions, turbulence, nervousness, price drops, risk aversion, investor caution, market instability, negative impact, market correction
Sentiment on corporate governance	Corporate ethics, governance views, board oversight, governance perception, accountability, transparency, ethical standards, shareholder rights, board oversight, governance practices, integrity, risk management, corporate responsibility, stakeholder engagement, code of conduct, governance framework, corporate culture, governance reforms, governance assessment, executive compensation
Sentiment on trade agreements	Trade optimism, trade deals, trade disputes, trade tensions, trade policy, global commerce, trade agreements, tariff negotiations, trade stability, trade diplomacy, trade tariffs, bilateral trade, trade war, trade balance, protectionism
Sentiment on currency markets	Exchange rates, currency market views, forex concerns, exchange rates, forex, foreign exchange, currency trading, currency pairs, forex analysis, currency valuation, currency strength, forex traders, currency fluctuations, forex market trends, currency speculation, currency volatility, currency risk, forex market outlook
Sentiment on financial health	Financial well-being, financial robustness, solvency, viability, liquidity, resilience, profitability, sustainability, well-being, asset quality, debt levels, capital adequacy, creditworthiness, financial stability, earnings potential
Positive	Optimistic, positivity, favourable, uplifting, excellent, innovative
Negative	Pessimistic, negativity, unfavourable, dismal, bankruptcy, discontinued, felony, loss, misstated
Litigious	Legal battles, lawsuit concerns, legal disputes, litigation worries, defendant, lawsuits, litigation, litigious environment, legal action, court cases, litigation risk, legal challenges, regulatory scrutiny, lawsuit-prone, legal proceedings, litigation costs, litigation strategy, legal consequences, litigation expenses, legal defence

Sentiments metrics	Lexicon
Aggregated sentiment	Summarized view, collective sentiment, composite outlook, overall sentiment
Interrogative sentiment	Questioning, inquiry, query, doubtful, investigation, examination, scrutiny, audit, assessment, review
Relative volume of talk (RVT)	Conversation intensity, chatter level, talk volume, discussion scale
Fear	Anxiety, panic, dread, apprehension, concern, tension, worry, trepidation, jitters
Related market measures	Market indicators, coordinated factors, benchmarks, metrics, economic indicators, financial benchmarks, performance measures, market statistics, market indices, performance metrics, comparative measures, market parameters, performance benchmarks, financial ratios

Funding The author(s) received no financial support for the research, authorship, and/or publication of this article.

Data availability The author confirms that all data generated or analysed during this study are available in the public domain website of SEBI, BSE, NSE, CMIE and Kaggle (Securities and Exchange Board of India 2023; Standard 2024; News 2024; India News Headlines Dataset 2024; Indian financial news articles (2003–2020) 2024; NSE 2023; BSE (formerly Bombay Stock Exchange) 2023; CMIE 2023).

Declarations

Conflict of interest The authors declare that there is no conflict of interest regarding the publication of this manuscript.

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